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Projected trends of soil organic carbon stocks in Meghalaya state of Northeast Himalayas, India. Implications for a policy perspective

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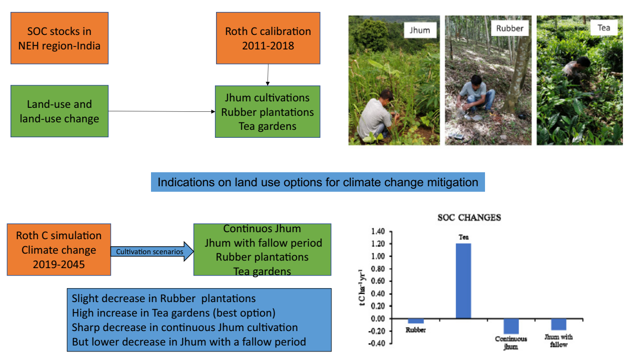
HIGHLIGHTS

- We studied jhum cultivations, rubber plantations and tea gardens.
- RothC was used to simulate SOC stocks after land use change and CC conditions.
- Simulations indicated that in rubber plantations SOC storage is limited in time.
- Tea gardens are the best option to increase SOC storage in a long-term perspective.
- Jhum cultivation with a secondary succession period can limit SOC decreases.

GRAPHICAL ABSTRACT



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ABSTRACT

Agricultural and forestry activities can affect soil organic carbon (SOC) levels and CO_2 emissions from terrestrial ecosystems due to land use changes. In Northeast Himalayas, studies on the effects of forest conversion to temporary agricultural lands (*jhum*) on the loss of SOC and soil quality degradation have received the attention of policy makers and scientific research. Presently, local communities are now oriented towards the settled plantations systems with modern cash crops such as tea and rubber, that could act as potential SOC sinks. However, no information on SOC dynamics and simulation studies after land-use change from temporary agricultural lands (*jhum*) to settled cultivations and under climate change (CC) conditions are available for the Meghalaya state. Applying the RothC model, we focused on four different scenarios including the conversion from *jhum* to settled cultivation (rubber plantations and tea gardens), as well as continuous *jhum* cultivation and *jhum* to *jhum* with a period of secondary succession. Simulations under CC conditions indicated that SOC stocks significantly increased by 1.20 t C ha^{-1} yr^{-1} in tea gardens compared to rubber and *jhum* scenarios. Conversely, SOC stocks slightly decreased by 0.07 t C ha^{-1} yr^{-1} in rubber plantations, while the regrowth of a natural vegetation cover as secondary succession following the abandonment of the *jhum* fields, showed a lower SOC decrease (0.18 t C ha^{-1} yr^{-1}) compared to the continuous *jhum* cultivation (0.24 t C ha^{-1} yr^{-1}). Thus, for CC mitigation in a policy perspective, tea gardens could represent the best land use to store increasing amounts of SOC in the long-term perspective and optimize farmers' incomes, while in rubber plantations SOC storage is limited in time. *Jhum* cultivation can benefit in terms of productivity and profitability by extending the duration of the secondary succession period.

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1. Introduction

The impact of climate change (CC) on natural resources has been studied at different levels worldwide and greenhouse gas emissions associated with anthropogenic activities, e.g. land-use change, are commonly recognized as a source of carbon dioxide (CO_2) emissions from soils (IPCC, 2014). Soil, if properly managed, is one of the best opportunities for carbon (C) sequestration from the atmospheric CO_2, through appropriate land-use approaches (Jha et al., 2012; Mujuru et al., 2013; Chenu et al., 2018). Intensive and non-sustainable practices under different land uses may deteriorate soil quality and soil organic matter status (Debiase et al., 2016; Novara et al., 2018). Agricultural and forestry activities are also known to affect soil organic carbon (SOC) levels and CO_2 emissions from terrestrial ecosystems due to land use changes (Grandy and Robertson, 2007; Francaviglia et al., 2012; Farina et al., 2017; Soleimani et al., 2019). SOC represents the two thirds of the Earth's carbon (Stockmann et al., 2013), and provides different essential soil functions, e.g. supporting the productivity of soils, maintaining or improving soil quality and SOC stocks for climate regulation, providing more protection from soil erosion, and increasing water regulation against floods and landslides (MEA, 2005; Scharlemann et al., 2014). In addition, SOC play a vital role in maintaining ecosystem health (Smith, 2016). Thus, the conservation of SOC stocks should be given the utmost priority, to ensure global food security and the prevention of substantial CO_2 losses (Wiesmeier et al., 2016).

The Northeast Himalayas (NEH) region of India is endowed with favorable climatic conditions and flourishing plant biomass, which makes this region unique in terms of biodiversity (Chatterjee et al., 2006). The NEH region has hot summers and cold winters, along with high rainfall areas, like Cherapunjee in the Meghalaya plateau receiving 11,000 mm rainfall, and land-use is greatly influenced by the hilly terrain with steep to very steep slopes (Choudhury et al., 2013; Behera et al., 2016). Furthermore, in the NEH region of India forest is the major land use pattern (65%), followed by agricultural land (16%); 86% of the total cultivated area falls under shifting cultivation (*jhum*) with slashing and burning of forest vegetation (Saha et al., 2012; Behera et al., 2016) and growing crops for household consumption for a variable period of time. Thereafter, *jhum* fields are abandoned and natural vegetation, as secondary succession, will regrow, while farmers will slash, burn and crop another secondary succession area (Mishra et al., 2017). Recently, studies on the effects of forest conversion to temporary agricultural lands (*jhum*) on the dynamics of SOC stocks and soil health have received the attention of policy makers and forest managers (Fearnside, 2000; IPCC, 2007). Mishra et al. (2019) recently reported about the negative changes (0.40 t C ha^{-1} yr^{-1}) in SOC stocks under *jhum* cultivation areas, in Dimapur and Kohima districts of Nagaland state, in NEH. To overcome this condition, local communities are now oriented towards the settled plantations systems (Teegalapalli and Datta, 2016) with modern cash crops such as tea (*Camellia sinensis* L.) and rubber (*Hevea brasiliensis* Muell. Arg.) and traditional cash crops, e.g. Broom grass (*Thysanolaena maxima*), areca nut (*Areca catechu*) and ginger (*Zingiber officinale*) (Behera et al., 2016). These land-use changes from temporary agriculture practices (*jhum*) to settled cultivations could act as potential new C sinks (Mukul et al., 2016). However, notwithstanding their importance to increase farmers' profitability, literature about SOC changes following the conversion from *jhum* to plantations with cash crops in NEH is scarce (Choudhury et al., 2016; Lungmuana et al., 2019).

Simulation models are increasingly applied worldwide to study the effect of land-use, land-use change and projected climate change conditions on SOC dynamics and greenhouse gases emissions (Brilli et al., 2017). Due to the many variables and processes involved in SOC dynamics, e.g. climate, soil, crop growth, soil management and SOC decomposition, simulation models have different degrees of complexity and requirements of input information. According to FAO (2019), RothC (Coleman and Jenkinson, 2014) has been one of the most widely used SOC models in the last 20 years. Compared to other simulations models, e.g. CENTURY (Parton et al., 1987), RothC requires few and easily available input data to run the simulations.

Unfortunately, studies related to SOC dynamics and their simulation, under land-use change from temporary agricultural lands (*jhum*) to settled cultivations are not available for the Meghalaya state, in NEH. In this study, we focused on four different scenarios including settled cultivation (conversion of *jhum* to rubber plantations and conversion of *jhum* to tea gardens), as well as continuous *jhum* cultivation and *jhum* to *jhum* hypothesizing 7 years of secondary succession period followed by *jhum* cultivation. Despite the limited number of soil samplings, the present study represents the first attempt to use the RothC model in different cropping scenarios in NEH. The specific objectives were as follows: i) simulating the changes in SOC stocks under different land use/land use change scenarios in a short term-period (2011–2018), ii) evaluating SOC changes under future climate change conditions (2019–2045), and iii) analyzing the projected SOC changes to provide a preliminary indication about the different land use options for climate change mitigation in a policy perspective.

2. Materials and methods

2.1. Study area

Meghalaya state in NEH is bounded to the south and west by Bangladesh and to the north and east by the Indian State of Assam. The state is part of the Indo-Malayan biogeographic realm, which includes the Indian subcontinent, Southeast Asia, and southern China, and harbors diverse biota with high level of endemism (Meghalaya State Climate Change Action Plan, 2015). The present study was conducted in Tura region of Garo hills, part of the Meghalaya subtropical forests ecoregion (Gillespie et al., 2012). Garo hills are located at 25°9′ - 26°1′ N latitude and 89°49′ - 91°2′ E longitude, occupy an area of 8167 km^2, and maximum elevation is 1412 m above mean sea level. Soils belong to Alfisols order, Udalfs suborder, Hapludalfs group, Ultic Hapludalfs subgroup (Soil Survey Staff, 2014). The major land use pattern of Garo hills is forests (5288.6 km^2), followed by agricultural land (1451.09 km^2). It was also reported that the area under *jhum* in Garo hills has increased to 2.52% (208.80 km^2 in 2013) from 0.79% (64.35 km^2 in 1991) (Sarma et al., 2016). To overcome forest degradation through the traditional *jhum* cultivation, the state government recommended the adoption of conservation management in arable crops and encouraged the cultivation of plantation crops like rubber, cashew nuts, etc. (Meghalaya State Climate Change Action Plan, 2015). This will not only act as a conservation measure against soil erosion and soil fertility loss, but also increase the income of farmers.

2.2. Sampling and analytical methods

A total of 16 sites were surveyed in 2010 by collecting soil samples (30 cm depth) from *jhum* land areas of Tura region in Garo hills (Figs. 1–2). Sampling depth is consistent with the IPCC guidelines to estimate the change in SOC stocks (IPCC, 2006). The selected *jhum* sites were chosen randomly within an area of about 78 km^2 and have similarity in terms of slope (between 5 and 10%) and relief (hilly and hilly uplands). At each site, one quadrat (10 × 10 m) was laid down and soil samples were collected from each corner. The collected soil samples were mixed in the field, to obtain a composite sample. The same sites were resurveyed and resampled in 2018 with the same sampling design, to evaluate the change in soil carbon stocks. However, it was observed that 9 sites had been converted to rubber plantations and 4

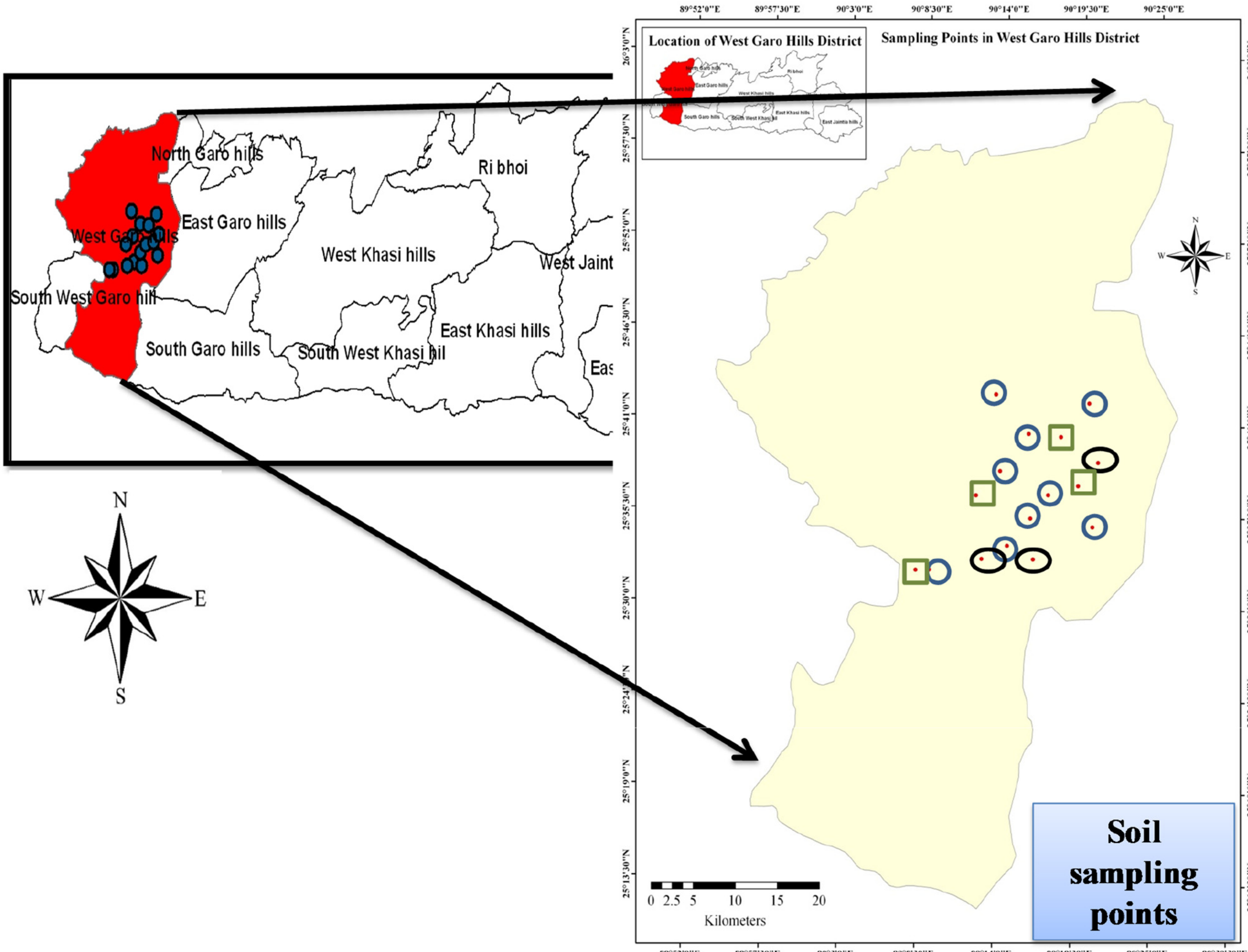

Fig. 1. Location of the sampling sites in West Garo hills District, Meghalaya. Blue circles and green squares indicate rubber plantations and tea gardens in 2018 respectively, black eclipses are sites still under *jhum* cultivation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

sites to tea gardens, respectively. The remaining 3 sites were still under *jhum* cultivation. Soil samples were air dried at room temperature (27–28 °C) for 3–4 days until constant weight. Visible plant materials were removed, and the analyses were made on the <2 mm dried soil fraction after sieving.

To assess the particle size distribution and bulk density (BD), methodologies given by Gee and Bauder (1986) and Blake and Hartge (1986) were employed, respectively. Soil pH was measured in soil water suspension (1:2.5) using a pH meter (Systronics pH System 361). The $K_2Cr_2O_7$ wet oxidation method given by Walkley and Black (1934) was used to estimate SOC content in soil. SOC stocks were calculated

Fig. 2. Soil sample collection from different land use systems. A: *jhum*; B: rubber plantation; C: tea garden.

with the following equation:

$$SOC = C\,(\%) \times BD \times D \qquad (1)$$

where, SOC = soil organic carbon stock (t C ha^{-1}), C = organic carbon content (%), BD = bulk density (g cm^{-3}), and D = depth (cm). Main soil parameters of sampling sites are shown in Table 1.

2.3. Climatic data

The 30-year (1987–2018) baseline climatic data of the Tura region, with the monthly values of average air temperature and precipitation, were obtained from the District and Local Research Station and Laboratories, West Garo hills district, Meghalaya state. Climate in Tura region is classified as warm and temperate, summers are much rainier than winters due to the monsoon rainy phase, and the Köppen-Geiger climate classification is Cwa. Average annual temperature is 24.6 °C and total rainfall is about 4000 mm. Climate change projections (2021–2050) based on the HadRM3 model were available from the Meghalaya State Climate Change Action Plan (2015). HadRM3 combines the HadCM3 global climate model (Pope et al., 2000) and the climate model PRECIS (Providing Regional Climates for Impacts Studies) widely used across the world including India (Rupa Kumar et al., 2006). PRECIS outputs, based on the SRES A1B mid-term (2021–2050) emission scenarios projections, are re-gridded at 0.2° × 0.2° resolution and aggregated at district level. Under climate change, projected average annual temperature is 26.4 °C and total rainfall about 4100 mm. Baseline and climate change patterns of annual precipitation and temperature are shown in Table 2.

2.4. The RothC model

RothC is designed to study the SOC turnover in non-waterlogged top soils (Coleman and Jenkinson, 2014). RothC is a single layer simulation model (normally 20–30 cm), thus neither simulates deep layers or changes in soil hydraulic/texture features with depth. The model can be run in two modes, i.e. direct and inverse. In the direct mode, SOC changes are calculated on C inputs defined by the model user, while in the inverse mode, also known as equilibrium state, SOC changes are automatically calculated by the model based on measured SOC stocks. SOC (t C ha^{-1}) is divided into four active pools, i.e. decomposable plant material (DPM), resistant plant material (RPM), microbial biomass C (BIO), and humified organic matter (HUM). In addition, the model considers a small amount of SOC resistant to decomposition, the inert organic matter (IOM) pool. Incoming plant C is split between DPM and RPM, depending on their ratio (DPM/RPM) in crop residues. Default values of the DPM/RPM ratio differ depending on the vegetation cover type and are 1.44 for agricultural crops and improved grasslands, 0.67 for unimproved grasslands and scrubs, and 0.25 for deciduous or tropical woodlands. SOC partitioning among the four active pools and decomposition to CO_2, BIO and HUM in RothC is described elsewhere (Mishra et al., 2019) and is synthetically shown in Fig. 3. IOM is automatically calculated from SOC stocks in the inverse mode with the formula proposed by Falloon et al. (1998). The model has an internal monthly step and requires a few input data based on monthly weather data, soil clay content, soil cover (bare or plant covered), quantity of C inputs from plant residues or farmyard manure (t C ha^{-1}), and DPM/RPM ratio (default or user defined). RothC is run setting up a simulation scenario based on two input data files. The land management file contains the monthly C inputs and the soil cover information. The weather file includes the monthly climatic data (temperature in °C, precipitation and open pan evaporation in mm), soil clay content in % and soil depth in cm. Open pan evaporation can be either measured (if available) or calculated from potential evapotranspiration using Thornthwaite and Mather (1955) equation. SOC decomposition rates are governed by plant C inputs and are nonlinear functions of temperature and soil moisture patterns. Clay content is used both to calculate plant available water and to regulate the partitioning between the CO_2 evolved and (BIO + HUM) formed during the decomposition of plant materials. Each of the four active compartments decomposes by first-order kinetics with an intrinsic maximum yearly default value of decomposition rate. The actual rate of decomposition is determined by modifiers for soil moisture, temperature (air temperature is used as a proxy of soil temperature) and soil cover, acting on the maximum decomposition rate (Coleman and Jenkinson, 2014). Modeled output data (on monthly or yearly scale) include DPM, RPM, microbial biomass C (BIO), humified organic matter (HUM), total SOC and CO_2 emissions.

2.5. SOC modeling

2.5.1. Equilibrium simulations

RothC was run in inverse mode (at equilibrium) on the 16 sampling sites that were under *jhum* cultivation in 2010, considering the measured total SOC stock (39.49 t C ha^{-1}), clay content (26.55%), average baseline climate conditions (1987–2010), the presence of vegetation cover in the *jhum* land use for eight months (from May to December) and setting the DPM/RPM ratio to the default value for arable crops (1.44). The inert organic matter (IOM) was automatically calculated by the model from the measured SOC stock (3.23 t C ha^{-1}), as well as the plant C inputs to be included in the land management file (6.50 t C ha^{-1}) required to match the measured SOC stock in the *jhum* land use in 2010.

2.5.2. Short-term simulations

After setting the equilibrium conditions of the *jhum* land use in 2010, RothC was run for eight years in the direct mode with a set of short-term simulation on four different scenarios of land use/land use change: conversion of *jhum* to rubber plantations (J to R), conversion of *jhum* to tea gardens (J to T), continuous *jhum* cultivation (Con J) and *jhum* to *jhum* (J7SJ) with 7 years of secondary succession period +1 year of *jhum* cultivation.

In the scenario J to R, the model was run in the direct mode with the aim to match the SOC stock in the rubber land use measured in 2018 (38.63 t C ha^{-1}), using the yearly baseline climate conditions (2011–2018). The C inputs required were manually calculated to simulate the establishment and growth of the rubber plantations, considering the presence of vegetation all over the year, and setting the DPM/RPM ratio to 0.25. Yearly C inputs (t C ha^{-1}) during the conversion of *jhum* to rubber plantations (J to R) were set as follows: 0 (2011), 1.25 (2012), 2.50 (2013–2014), 3.75 (2015), 5.00 (2016–2018).

In the scenario J to T, the model was run in the direct mode to match the SOC stock in the tea land use measured in 2018 (45.09 t C ha^{-1}),

Table 1
Main soil parameters for the land uses (sampling years). Data are referred to 30 cm (means ± SD).

Land use	n	Bulk density (g cm^{-3})	pH	Silt (%)	Clay (%)	Sand (%)	SOC (%)	SOC (t C ha^{-1})
Jhum (2010)	16	0.88 ± 0.04	5.13 ± 0.35	19.10 ± 12.95	26.55 ± 9.47	54.36 ± 9.54	1.50 ± 0.42	39.49 ± 10.63
Rubber (2018)	9	0.88 ± 0.03	5.14 ± 0.49	19.41 ± 4.90	28.42 ± 7.86	52.17 ± 6.97	1.47 ± 0.18	38.63 ± 4.60
Tea (2018)	4	0.88 ± 0.03	5.00 ± 0.14	16.65 ± 2.93	33.95 ± 13.00	49.40 ± 15.42	1.72 ± 0.17	45.09 ± 4.06
Jhum (2018)	3	0.91 ± 0.03	5.07 ± 0.55	15.63 ± 1.53	25.03 ± 6.29	59.33 ± 7.58	1.31 ± 0.17	35.55 ± 3.43

SD standard deviation, SOC soil organic carbon. Differences among soil parameters in 2010 and 2018 were not significant ($p < 0.05$) among land uses (Tukey HSD post-hoc test).

Table 2
Mean annual temperature, precipitation and open pan evaporation under the baseline climate (1987–2018) and climate change projections (2021–2050) for Tura region (Garo hills, Meghalaya state).

Month	Average climate 1987–2018			Average climate change 2021–2050		
	Temperature °C	Precipitation mm	Open pan mm	Temperature °C	Precipitation mm	Open pan mm
January	19.8	16.1	67.2	21.7	16.5	78.0
February	22.1	17.3	89.7	23.9	17.7	107.1
March	24.4	64.8	143.7	26.2	66.4	176.7
April	25.9	275.1	178.7	27.8	281.9	224.0
May	25.9	539.8	194.3	27.8	553.3	243.7
June	25.8	797.8	190.5	27.6	817.7	238.4
July	26.0	839.0	198.7	27.8	860.0	249.3
August	26.1	636.3	193.7	28.0	652.2	243.5
September	26.4	509.7	183.0	28.3	522.4	231.0
October	26.0	283.4	169.1	27.9	290.5	212.3
November	24.4	16.4	127.4	26.3	16.8	156.7
December	21.7	6.6	88.5	23.6	6.8	105.2
Year	24.6	4002.2	1824.5	26.4	4102.3	2265.7

using the yearly baseline climate conditions (2011–2018). The C inputs required were manually calculated to simulate the growth of the tea gardens, considering the presence of vegetation all over the year, and setting the DPM/RPM ratio to 1.44. Yearly C inputs (t C ha^{-1}) during the conversion of *jhum* to tea gardens (J to T) were set as follows: 2.38 (2011), 4.75 (2012), 7.13 (2013), 9.50 (2014–2018).

In the scenario continuous *jhum* cultivation (Con J), the model was run in the direct mode to match the SOC stock in *jhum* land use measured in 2018 (35.55 t C ha^{-1}), using the yearly baseline climate conditions (2011–2018). The C inputs required were manually calculated to simulate the continuous *jhum* cultivation, considering the presence of vegetation cover in the *jhum* land use for eight months (from May to December) and setting the DPM/RPM ratio to 1.44. Yearly C inputs during the continuous *jhum* cultivation (Con J) were set to 4.20 t C ha^{-1}.

In the scenario *jhum* to *jhum* (J7SJ), we hypothesized 7 years of secondary succession period, that is the most common average duration before a new *jhum* cropping cycle is started, followed by 1 year of *jhum* cultivation. The model was run in the direct mode to match the SOC stock in *jhum* land use measured in 2018 (35.55 t C ha^{-1}), using the yearly baseline climate conditions (2011–2018). The C inputs required were manually calculated firstly to simulate the secondary succession period, with the establishment of natural vegetation, considering the presence of vegetation all over the year, and setting the DPM/RPM ratio to 0.25. Yearly C inputs in the secondary succession period were set to 3.90 t C ha^{-1}. Thereafter, the C inputs required were manually calculated to simulate the setup of a new *jhum* cultivation, considering the presence of vegetation cover in the *jhum* land use for eight months (from May to December) and setting the DPM/RPM ratio to 1.44. Yearly C inputs in the *jhum* period were set to 2.40 t C ha^{-1}.

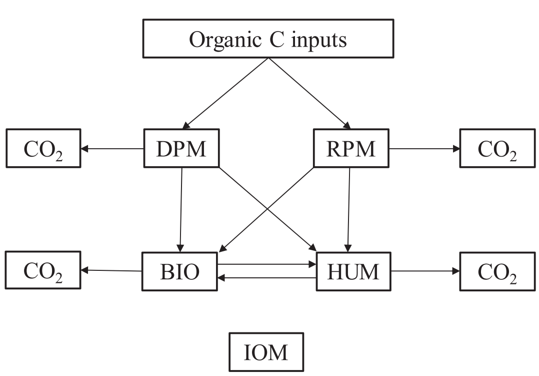

Fig. 3. Partitioning and decomposition of organic C inputs in RothC (modified from Mishra et al., 2019). DPM = decomposable plant material, RPM = resistant plant material, BIO = microbial biomass carbon, HUM = humified organic matter, CO_2 = carbon dioxide emitted during decomposition, IOM = inert organic matter.

2.5.3. Statistical analysis

The agreement of the short-term model predictions with the values of SOC stocks measured in 2018 in the different scenarios (J to R, J to T, Con J and J7SJ) was tested using the mean absolute error (MAE), the root mean square error (RMSE) and the modeling efficiency (EF):

$$MAE = \frac{\sum_{i=1}^{n} |(O_i - S_i)|}{n} \tag{2}$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2\right]^{1/2} \tag{3}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2} \tag{4}$$

where, S_i and O_i are the ith simulated and observed SOC values respectively, $\overline{O}$ the average observed SOC, and n the total number of observations.

Both MAE and RMSE express average model prediction error in the same units of the variable of interest. The best value of both MAE and RMSE is zero, indicating a perfect agreement between simulated and observed data. MAE can be lower or equal to RMSE, and RMSE values should be not higher than the standard deviation of the observed data (Smith and Smith, 2007). EF can range from $-\infty$ to 1, and the best performance is EF = 1.

Differences of soil parameters and SOC stock changes among land-uses were analyzed using One-way ANOVA and significant differences among means ($p < 0.05$) were evaluated through the Tukey HSD post-hoc test. Statistical analyses were performed using the software Statistica 8.0 (Statsoft, Tulsa, USA).

2.5.4. Climate change simulations

After running RothC with the short-term simulations previously described (see Section 2.5.2), the model was run under climate change conditions for 27 years from 2019 to 2045 (see Section 2.3), with the same parametrization for C inputs and decomposability of plant material (DPM/RPM). The aim of the study was to provide a preliminary indication about the different land use options for climate change mitigation in a policy perspective in relation to SOC dynamics, considering the four cropping scenarios (J to R, J to T, Con J and J7SJ) in future projected climatic conditions.

3. Results

3.1. Measured SOC stocks

Average SOC stock measured in 2010 in the sampling sites under *jhum* cultivation was 39.49 ± 10.63 t C ha^{-1}. Average SOC stocks measured in 2018 were 38.63 ± 4.60 t C ha^{-1} in the rubber plantations, 45.09 ± 4.06 t C ha^{-1} in the tea gardens, and 35.55 ± 3.43 t C ha^{-1} in the *jhum* sites. No significant differences in SOC stocks were found among the considered land uses in 2010 and 2018. Compared to 2010, average SOC stock in the rubber plantations slightly decreased by 0.86 t C ha^{-1} (2.2%), increased by 5.60 t C ha^{-1} (14.2%) in tea gardens, and decreased by 3.94 t C ha^{-1} (10.0%) in *jhum* sites (Table 1).

3.2. Equilibrium and short-term simulations

When running RothC at equilibrium on *jhum* sites in 2010 (Table 3), a C input equal to 6.50 t C ha^{-1} was required to match the measured SOC value in this land use (39.49 t C ha^{-1}).

In the scenario with the conversion of *jhum* to rubber plantations (Table 3), the model calibration with a short-term simulation (2011–2018) required a C input in rubber plantations equal to 5 t C ha^{-1} at full development to match the SOC stock measured in 2018 (38.63 t C ha^{-1}). The simulated SOC stock in 2018 for this scenario was 38.46 t C ha^{-1}.

In the scenario with the conversion of *jhum* to tea gardens (Table 3), the model calibration with a short-term simulation (2011–2018) required a C input in tea gardens equal to 9.5 t C ha^{-1} at full development to match the SOC stock measured in 2018 (45.09 t C ha^{-1}). The simulated SOC stock in 2018 for this scenario was 44.99 t C ha^{-1}.

In the scenario with continuous *jhum* cultivation (Table 3), the model calibration with a short-term simulation (2011–2018) required a C input equal to 4.20 t C ha^{-1} to match the SOC stock measured in 2018 (35.55 t C ha^{-1}). The simulated SOC stock in 2018 for this scenario was 35.45 t C ha^{-1} and the calibrated C input, equal to 65% of *jhum* at equilibrium, was set to consider that continuous *jhum* cultivation negatively affects both soil quality and crop yield. The simulated SOC stock in 2018 for this scenario was 35.45 t C ha^{-1}.

In the scenario *jhum* to *jhum* (Table 3), with 7 years of secondary succession period +1 year of *jhum* cultivation, the model calibration with a short-term simulation (2011–2018) required a C input equal to 3.90 t C ha^{-1} in the secondary succession phase, and to 2.40 t C ha^{-1} in the *jhum* period to match the SOC stock measured in 2018 (35.55 t C ha^{-1}). The simulated SOC stock in 2018 for this scenario was 36.45 t C ha^{-1}.

3.3. Model evaluation

The short-term simulations of the four scenarios were validated based on MAE, RMSE and EF (Table 3). In the scenario with the conversion of *jhum* to rubber plantations, MAE, RMSE and EF were 0.167, 0.500 and 0.985 respectively, and the standard deviation of the measured values (4.60 t C ha^{-1}) was higher than RMSE. In the scenario with the conversion of *jhum* to tea gardens, MAE, RMSE and EF were 0.104, 0.207 and 0.997 respectively, and the standard deviation of the measured values (4.06 t C ha^{-1}) was higher than RMSE. In the scenario with continuous *jhum* cultivation, MAE, RMSE and EF were 0.098, 0.170 and 0.996 respectively, and the standard deviation of the measured values (3.43 t C ha^{-1}) was higher than RMSE. In the scenario *jhum* to *jhum*, with 7 years of secondary succession period +1 year of *jhum* cultivation, MAE, RMSE and EF were 0.002, 0.003 and 1.000 respectively, and the standard deviation of the measured values (3.43 t C ha^{-1}) was higher than RMSE.

Results indicate that the agreement between measured and simulated data was quite accurate, and the RothC model can be used to simulate SOC stock dynamics in the four cultivation scenarios under the climate change conditions.

3.4. Climate change simulations

All simulation under climate change refer to a period of 27 years, from 2019 to 2045 (Fig. 4). In the scenario with the conversion of *jhum* to rubber plantations (J to R) SOC slightly decreased by 1.78 t C ha^{-1}, from 38.46 in 2018 to 36.68 t C ha^{-1} in 2045, equal to −0.07 t C ha^{-1} yr^{-1}. In the scenario with the conversion of *jhum* to tea gardens (J to R) a high SOC increase of 7.19 t C ha^{-1} was observed, from 44.99 in 2018 to 52.18 t C ha^{-1} in 2045, equal to 0.30 t C ha^{-1} yr^{-1}. The scenario with continuous *jhum* cultivation (Con J) showed the highest SOC decrease equal to 6.35 t C ha^{-1}, from 35.45 in 2018 to 29.10 t C ha^{-1} in 2045, equal to −0.24 t C ha^{-1} yr^{-1}. A lower SOC decrease of 4.77 t C ha^{-1} was observed in the scenario J7SJ with 7 years of secondary succession and 2 years of *jhum* (9 years cycle), from 36.45 in 2018 to 31.68 t C ha^{-1} in 2045, equal to −0.18 t C ha^{-1} yr^{-1}.

4. Discussion

The conversion of natural ecosystems to agricultural land use negatively affects SOC stocks, and SOC loss is generally higher in tropical areas compared to temperate regions (Wairiu and Lal, 2003). Even if C inputs are generally higher under humid conditions than in semi-arid regions, Woomer et al. (1994) indicated that SOC does not increase due to the faster turnover rates and the enhanced microbial activity in

Table 3
Equilibrium (jhum 2010) and calibrated results of short-term model simulations for the different LULUC (land use/land use change) scenarios.

LULUC[a]	Average SOC (t C ha^{-1})		IOM (t C ha^{-1})	C inputs (t C ha^{-1})	DPM/RPM	MAE	RMSE	EF
	Measured	Simulated						
J2010	39.49	39.49[b]	3.23	6.50[b]	1.44	–	–	–
JtoR	38.63	38.46[c]	–	5.00[d]	0.25	0.167	0.500	0.985
JtoT	45.09	44.99[c]	–	9.50[e]	1.44	0.104	0.207	0.997
ConJ	35.55	35.45[c]	–	4.20[f]	1.44	0.098	0.170	0.996
J7SJ	35.55	36.45[c]	–	3.90/2.40[g]	0.25/1.44[h]	0.002	0.003	1.000

SOC soil organic carbon; IOM Inert Organic Matter; DPM/RPM ratio of decomposable plant material to resistant plant material; MAE Mean Absolute Error; RMSE Root Mean Square Error; EF Modeling Efficiency.

[a] J2010 jhum at equilibrium, JtoR scenario with conversion of jhum to rubber, JtoT scenario with conversion of jhum to tea, ConJ continuos jhum, J7SJ scenario jhum to jhum (7-yr secondary succession period + 1 yr jhum cultivation).

[b] Model run to equilibrium in "inverse mode".

[c] Model calibrated after equilibrium from J2010.

[d] Rubber C inputs: 0 (2011), 1.25 (2012), 2.50 (2013–2014), 3.75 (2015), 5.00 (2016 onwards).

[e] Tea C inputs: 2.38 (2011), 4.75 (2012), 7.13 (2013), 9.50 (2014 onwards).

[f] Continuous jhum C inputs: 4.20 (65% of jhum cultivation at equilibrium).

[g] Jhum to jhum (7-yr secondary succession period + 1 yr jhum cultivation) C inputs: 3.90 (secondary succession period), 2.40 (1 yr jhum cultivation).

[h] DPM/RPM: 0.25 (secondary succession), 1.44 (jhum).

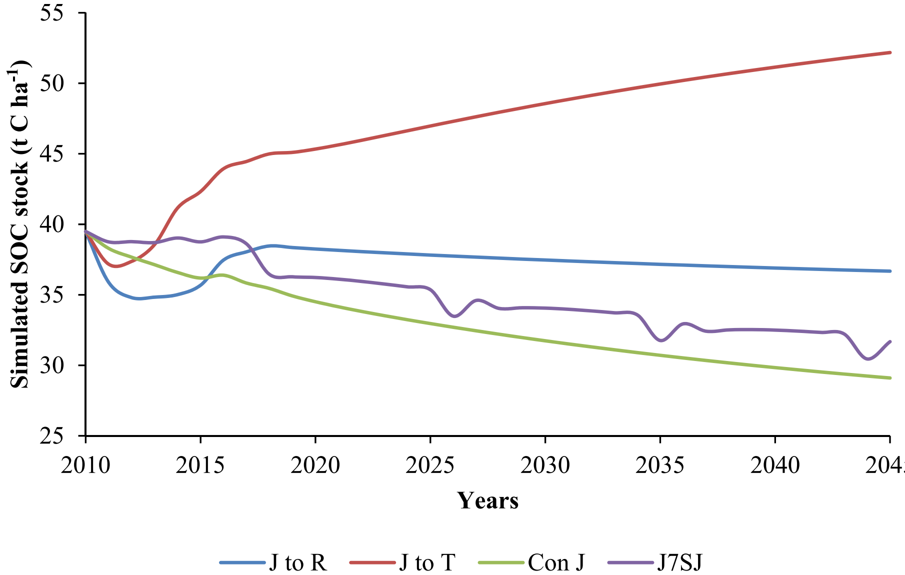

Fig. 4. Simulated SOC dynamics under the baseline (2011–2018) and climate change conditions (2019–2045) for the different scenarios. J to R, conversion of *jhum* to rubber plantations; J to T, conversion of *jhum* to tea gardens; Con J, continuous *jhum* cultivation; J7SJ, *jhum* to *jhum* (secondary succession period + *jhum* cultivation).

these peculiar conditions. Moreover, SOC losses are usually high in *jhum* cultivation, particularly when the secondary succession period between *jhum* cycles is reduced and crop residues are removed from the field (Wairiu and Lal, 2003). In our study, the average rate of SOC stock decrease in the *jhum* cultivation was 0.49 t C ha^{-1} yr^{-1} under the baseline climate conditions (2011–2018). The modeled C input is consistent with the average data for *jhum* cultivations reported by Mishra et al. (2019) in Nagaland state of NEH of India, equal to 5.82 (range 5.0–6.6) t C ha^{-1}. Measured SOC stocks in *jhum* cultivation were also considerably lower compared to natural ecosystems (forest sites) previously investigated in NEH (Mishra et al., 2017, 2019). When simulating the scenario with continuous *jhum* cultivation under climate change conditions (2019–2045), average SOC stocks decreased by 0.24 t C ha^{-1} yr^{-1} in 27 years. This result is not contrasting with the higher decrease under the baseline climate. In fact, Mishra et al. (2019) indicated that SOC decrease was inversely related to the length of the *jhum* cycle, almost linear in the first years and thereafter slightly decreasing. Anyhow, results of simulations under climate change also indicated that the regrowth of a natural vegetation cover as secondary succession, following the abandonment of the *jhum* fields, showed a lower but not significant SOC decrease (0.18 t C ha^{-1} yr^{-1}) compared to the continuous *jhum* cultivation.

In relation to rubber plantations, measured SOC stocks in 2018 were higher but not significantly different compared to the *jhum* sites (38.63 vs 35.55 t C ha^{-1}). Model calibration to simulate the trend of SOC stocks after the conversion from *jhum* to rubber plantations during the period 2011–2018 was in good agreement with the measured data (38.46 t C ha^{-1}) and the calibrated C input is in good agreement with the data reported by Liu et al. (2017) equal to 4 t C ha^{-1} for 7-year-old rubber plantations in tropical China. In addition, simulations under climate change conditions indicated an average slight decrease by 1.78 t C ha^{-1} in 27 years (−0.07 t C ha^{-1} yr^{-1}) but not significantly different compared to the *jhum* sites, that can be considered almost a steady-state condition. Bruun et al. (2018) studied SOC stocks in rubber plantations converted from *jhum* cultivations in northern Laos under subtropical monsoon climate conditions. Considering rubber plantations of different ages after the establishment, SOC stocks (0–25 cm) decreased by 8.9 t C ha^{-1} in older rubber plantations (7–10 years old) compared to recently established plantations (2–3 years old). SOC further decreased by 2.7 t C ha^{-1} in rubber plantations that were 17–18 years old. The same authors (Bruun et al., 2018) also concluded that conversion from *jhum* to rubber plantations leads to an increase of SOC stocks after the first years following the establishment, but to a net SOC loss when the rubber plantation was mature. Conversely, Lungmuana et al. (2019) reported an increase in SOC stocks after the conversion of *jhum* to rubber plantations about 15 years old in Mizoram state of NEH (India), with a high contribution of microbial biomass C to SOC.

Finally, SOC stocks in tea gardens in 2018 (45.09 t C ha^{-1}) were higher but not significantly different compared with sites under *jhum* cultivation (35.55 t C ha^{-1}) and rubber plantations (38.63 t C ha^{-1}), increased by 1.20 t C ha^{-1} yr^{-1} and the simulated SOC stock (44.99 t C ha^{-1}) was in good agreement with the measured data. The calibrated C input is in good agreement with the data reported by Kalita (2015) equal to 9.1 t C ha^{-1} for tea gardens in Assam (India). Under climate change conditions, SOC stocks significantly increased by 7.19 t C ha^{-1} in 27 years (0.30 t C ha^{-1} yr^{-1}) compared to *jhum* and rubber land uses. The higher SOC stocks in tea gardens mainly depends on a set of factors (Leon et al., 2015). Firstly, soil pH should be within the optimal range for tea growth (4–5.5), thus increasing yields and plant C inputs to the soil through the litterfall. And in our study soil pH in tea gardens was 5.0. Secondly, SOC increases have been generally associated with slower decomposition rates when soil reaction is acid (Dutta et al., 2008). Furthermore, farmers leave the trimmed branches in the tea gardens, and soil C can increase with stand age (Pansombat et al., 1997; Li et al., 2011). Chiti et al. (2018) also reported that SOC stock still increased with time in tea gardens after 31 and 43 years since the establishment in a tropical montane site in Kenya.

This is the first approach to model SOC dynamics under climate change conditions covering a peculiar set of cropping scenarios including different options of land use. The study focused on land use change following the conversion of *jhum* sites (firstly sampled in 2010) to other land uses with modern cash crops (rubber and tea) as indicated during the resampling in 2018. The low number of soil samplings (16 sites) is an implicit limitation of the study, that was carried out under different projects, but was constrained by limitations of time for field surveys and staff available for sampling. However, we considered this land use change a unique opportunity, that might not happen again, to provide an insight into SOC changes following a very important land use conversion in a long-term and policy perspective.

Other inherent uncertainties can derive from the use of a simulation model to study SOC dynamics, since all models show positive and negative features, and from climate change projections since in all simulation models climate parameters (through temperature and soil moisture patterns) have a primary influence on predicted SOC stocks.

In the case of RothC simulations, further uncertainties might derive from the assumption that C inputs were kept constant under climate change conditions, while could actually be positively affected by the increase in crop biomass and residues due to the combined effect of CO_2 fertilization and higher future temperatures. However, setting higher or lower C inputs under climate change conditions would be quite arbitrary and neither supported by specific scientific findings.

5. Conclusions

In different states of the NEH region of India, the high demographic change has modified the traditional agricultural land-use through the conversion of the slash and burn cultivations (*jhum*) to cash-cropping systems that increase commercialization opportunities and profits. In the present study we analyzed SOC dynamics in different cultivation scenarios under future climate change conditions, based on the conversion of *jhum* to rubber plantations and tea gardens, as well as two options for the maintenance of *jhum* cultivation.

Based on the results of this study, we can provide some preliminary indications about the different land use options for climate change mitigation in a policy perspective. SOC stock increase after the conversion of *jhum* cultivation to rubber is limited in time and decrease with the plantation age, thus rubber plantations should have a short duration. Conversely, the conversion of *jhum* cultivation to tea gardens is the best option to store increasing amounts of SOC in the long-term perspective and optimize farmers' incomes.

Farmers adopting frequent *jhum* cultivation cycles on the same field can benefit in terms of productivity and profitability by extending the duration of the secondary succession period, specifically 7 years of secondary succession period followed by 2 years of *jhum* cultivation, with lower even if not significantly different SOC losses compared to the continuous *jhum* cultivation.

Declaration of competing interest

The authors declare they have no conflict of interest.

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